Chapter 16
Event quality awareness for contextualized decision support in e-health applications

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Abstract This chapter introduces contextualization of events as means to improve decision support systems in clinical environments. Modern hospitals are full of technology producing electronic records of events and activities, each meaningful in their specific context. This creates the opportunity to culminate these events into a wealth of information that we can tap into to take better informed decisions and facilitate coordination. By means of a problem frame analysis of a use case in a hospital setting, we motivate the importance of event contextualization. We explain and evaluate how the quality of these events impact decision making when changes to a pre-set patient trajectory occur.

16.1 Introduction

This chapter focuses on context-awareness in the e-health domain with a case study on the patient trajectory as a clinical process in a hospital setting. We define a patient trajectory as a timeline-oriented representation of what actually has occurred and will happen with the patient during encounters with clinicians. Through inspecting a patient trajectory, a clinician can see how far the plan concerning a patient has progressed, and also whether there have been deviations from the original plan. Based on this information, he can decide if he needs to make any adjustments to

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his own activities. Given the distributed nature of many hospital systems, the events they produce, and the lack of their contextual relevance on an overall level, it is hard for a clinician to gain an overview over the current overall patient status.

In this chapter we introduce a notion on the quality of the context information that these events carry as this is of vital importance to make well-informed decisions. However, as the events are meant to be used within their set context, combining events from different sources and different contexts will have an impact on the quality of the information upon which decisions are based. Furthermore, hospitals are required to cope with an assortment of compliance regulations that constrain the way patients and healthcare professionals can be tagged and tracked to collect information about their whereabouts and circumstances. One of the challenges is to infer the location of the stakeholders by the events generated in the various underlying systems instead of simply being able to tap into a location service. Events from the same source and even with the same value can have different interpretations depending on more or less implicit context.

To crisply identity the main problems to be solved, we carried out a domain analysis using the *problem frame* method [7]. Jackson describes it as follows: *"problem analysis considers a software application to be a kind of software* machine. *A software development project aims to change the problem context by creating a software machine and adding it to the problem context, where it will bring about certain desired effects. The particular portion of the problem context that is of interest in connection with a particular problem - the particular portion of the problem context that forms the context of the problem - is called the application domain."*

Through observations in the field and various discussions with medical stakeholders, we found that a system for helping to get an accurate overview of the situation was very desirable and we elicited the following key concerns:

1. **Non-deterministic occurrence of events:** With some systems operating in isolation, not every event in the real world can be represented with a digital event. The order of events is often undetermined, and from a medical point of view the exceptions are more interesting than common fixed patterns.
2. **Context-dependent meaning of events:** Two similarly looking events produced by the same system can have a totally different meaning. Their interpretation is subject to the current context, previous events and those that are about to occur.
3. **Quality awareness in events:** The inference of complex events should account for the quality of information of its constituents. The quality of an event (probability of occurrence, reliability, relevance, etc.) may vary over time and influence the confidence in the value of an encompassing complex event.

We define a contextualized event as a complex event semantically enriched through situational refinement. The quality of a contextualized event can be justified by detecting patterns based on historical data, or gather additional information from pseudostatic sources such as calendar or planning systems. Contextualized events can continuously be upgraded or degraded based on new knowledge affecting the quality indicator. Our goal is to contextualize events to make sure that event streams are correctly interpreted. We therefore introduce the notion of *Quality of Event*:

Quality of Event: is a quality measure for the validity of events of how well they characterize activities in the real world. The measure combines the following quality attributes: (1) q_p, the *probability* that the related activity has occurred, (2) q_r, the *reliability* that the order and the information the individual events carry are correct, (3) q_c, the *contextual relevance* (e.g. time, space, semantics) for being retained as a significant constituent in a complex event pattern (representing an activity).

For a more detailed description of the Quality of Event, we refer to our previous work [16]. After a short background about the field, this chapter will first introduce a real-world case study of several diagnostic activities in a patient's trajectory taking place at a Norwegian hospital. This case stems from the COSTT[1] project. Tackling the challenge of the non-deterministic nature of healthcare processes is instrumental to realizing a system that can cope not only with the majority of regular cases - but also recognize the minority of cases with deviations in event values. The main contributions of this chapter can be summarized as follows:

- Insights into applying context in an a-typical application domain
- Demonstration with a real-world use case on patient trajectories at a hospital
- Reusable concepts and lessons learned for context quality management

The feasibility and effectiveness of our framework for contextualized decision support system has been tested on top of the SAMURAI system[2], a *Streaming Architecture for Mobile and Ubiquitous RESTful Analysis and Intelligence*. This system was partly developed and evaluated in the frame of the FP7 BUTLER[3] project.

16.2 Background and related work

Variability is a key characteristic of clinical work [14, 3, 1]. This variability is a result of hospitals becoming larger, as well as the growing complexity in the organizational structure, new technology and treatments. Furthermore, with incoming emergency cases pre-empting planned work as well as the outcome of treatments not going according to expectations, hospitals need to deal with a continuous stream of unforeseen, though somehow expected interruptions to their routine work. To cope with these challenges, health care professionals need up-to-date information about the state of the processes in their immediacy. The increased use of technology enables a growing availability of streams of system events that can be tapped into for better informed decisions and coordination, though the ambiguous nature of raw data taken out if its context makes this a challenging endeavor.

Lee et al. [10] investigated data fusion in pervasive healthcare monitoring systems (PHMS), and identified similar challenges regarding collecting and aggregating events from body sensor networks, wireless sensor networks and mobile devices. The rate of collected data in medical sensor networks is increasing, and so is the

[1] http://www.ntnu.no/nsep/costt

[2] https://butler.cs.kuleuven.be/samurai/

[3] http://www.iot-butler.eu

complexity to produce high confidence data for medical diagnosis and treatment. They address the reliability of measured data by body sensors and communicating the data over heterogeneous wireless networks. Wasserkrug et al. [15] carried out similar work on uncertainty in complex event streams. They confirm that most contemporary event composition systems are unable to handle incomplete or uncertain information. Their framework not only handles uncertain events, but also the uncertainty in the inference process. They consider a temporal context and which events are relevant to the inference of other events.

Context-aware applications depend on the availability of context information at the right time and place and in the right quality. Buchholz et al. [4] argued on the importance of Quality of Context (QoC) for real-life applications to make effective use of provided context information. The QoC is any information that describes the quality of the information that is used as context information. As such, it is a quality parameter that more relates to the precision, the probability of correctness, the accuracy and up-to-dateness of context information. Intensive research has been carried out in the domain of modeling quality of context information. Work by Buchholz et al. [4], Henricksen et al. [6] and Manzoor et al. [11] defined several quality metrics for context information and other authors like Krause et al. [9], Sheikh et al. [13] and Abid et al. [2] have further added to these parameters. In our work, we introduce a similar notion, specifically for events and event-based information systems.

16.3 Use case scenario of patient assessment activities

The domain knowledge and the concrete use case behind this article was acquired through observations of a pre-operative medical evaluation for cardiac patients in a Norwegian University Hospital Clinic (though do note that we have tried to keep the scenario at a level understandable for an audience without any form of medical training and therefore we needed to make some simplifications or minor changes to the scenario). To reduce the inconvenience for the patients, what used to be seven or eight examinations over several visits to the hospital has been compressed into one full day of examination activities. While this is beneficial to the patient, it increases the complexity on behalf of the hospital by increasing the need for timely coordination and communication in order to execute this plan. Problems that earlier could be sorted out between visits, will now have to be coordinated on the spot.

As patients in our scenario undergo the same examinations by the same medical stakeholders, a variation in the time used versus the time planned will impact the consultation of the other patients. General event patterns can be created, though the temporal order may vary from patient to patient. As each of the activities generate events that map to the temporal ordering and the pattern, one can get a fair impression of the progress of a patient while he/she traverses all activities.

During the examination day, the patient has to undergo a number of standardized tests (e.g. laboratory tests, radiologic exam, ECG) in a more or less pre-determined chronological order, see Fig. 16.1. The list in Table 16.1 is a non-exhaustive list of

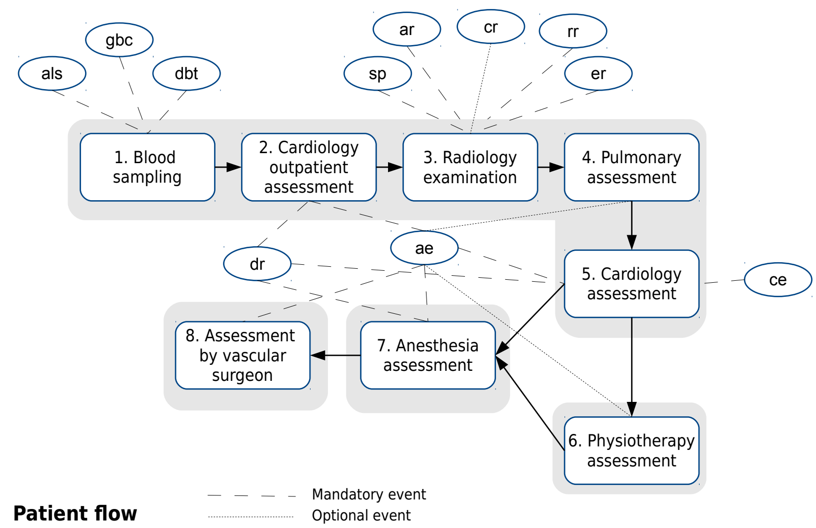

Fig. 16.1 Typical flow of patient activities and corresponding events

	Event	Description
ae	*AccessEPR(r, p)*	The Electronic Patient Record of patient *p* has been accessed by someone with role *r* (typically a medical doctor).
als	*AccessLabSystem(p)*	The Lab System has been accessed for patient *p*.
ar	*AccessRIS(r, p)*	The Radiology Information System has been accessed for patient *p* by medical staff with role *r*.
ce	*CardioEcho(p)*	A cardio echo regarding patient *p* has been stored.
cr	*ChangeRIS(r, p)*	Information in the Radiology Information System has been changed for patient *p* by medical staff with role *r*.
dbt	*DispatchBloodTest(p)*	A blood sample containing a sample of blood from patient *p* has been sent by tube mail.
dr	*DictateResult(r, p)*	Medical staff with role *r* has dictated a voice note regarding patient *p*.
er	*ExaminationReady(r, p)*	A staff member with role *r* at the radiology department has finished the examination of patient *p*.
gbc	*GenerateBarCode(p)*	A bar code with patient information of patient *p* has been generated.
rr	*ReportReady(r, p)*	A staff member with role *r* at the radiology department has finished the report regarding patient *p*.
sp	*StoreInPACS(r, p)*	Information regarding patient *p* has been stored in the picture archiving and communication system by medical staff with role *r*.

Table 16.1 Description of associated events

events, though rather a selection of reasonably reliable and obtainable events that can be captured in order to be able to detect that this particular activity is going on. In Table 16.2 we have described the main activities and corresponding events over the course of such a day. In our notation, the “;” operator denotes a sequence of events, and “?” the presence of an optional event.

The order in which events occur often follows a predefined workflow path, which could be seen as an event pattern. The order in which events occur can differ based on the workflow path chosen. The ideal ordering of standard tests a patient typically has to undergo during the examination day can be represented as follows:

	Activity	Description	Pattern
A_1	Blood samples	are obtained for screening blood values, which could indicate patient conditions that need to be controlled to mitigate risk and ensure safe surgery.	als ; gbc ; dbt
A_2	Cardiology outpatient assessment	to assess the suitability of the patient for surgical intervention with respect to the functioning of the patient's circulatory system. This includes an income interview and an *echo-Doppler* examination	ae ; dr
A_3	Radiology examination	where x-ray imagery is used to help assess the suitability for operation. This also serves as input for the anaesthetist assessment later in the day	ar (; cr?) ; sp ; er ; rr
A_4	Pulmonary assessment	including a spirometry test. This is in essence a measurement of the amount (volume) and/or speed (flow) of air that can be inhaled and exhaled, and used to assess lung function. This is input for the anesthetists and vascular surgeon's assessment.	(ae)?
A_5	Cardiology assessment	to assess the heart function of the patient for suitability for operation	ae ; ce ; dr
A_6	Physiotherapy assessment	is undertaken for some specific diagnoses. The patient sees a cardiopulmonary physiotherapist for an assessment	(ae)?
A_7	Anesthesia assessment	is conducted to evaluate and score, the patient according to a standardized set of criteria, partly based on the information collected throughout the day. It is also meant to give the patient an opportunity to ask questions to ease any discomfort the patient has about being anesthetized and allow the anesthesiologist to make an evaluation of which form of anesthesia is to be used.	ae ; dr
A_8	Assessment by vascular surgeon	is the final point of the day where the patient has a consultation with a vascular surgeon. This gives the surgeon a last opportunity to make any additional examinations and the final evaluation based on all the data gathered during the day as well as an opportunity for the patient to ask questions about his or hers own illness and any discomfort about undergoing surgery.	ae

Table 16.2 Activities during a patient assessment and associated events

$$A_2;A_5 \tag{16.1}$$

$$\{A_1,A_2,A_3,A_4,A_5\} \quad (;A_6)? \quad ;A_7 \quad ;A_8 \tag{16.2}$$

It shows that the first 5 activities can be carried out in any order, except for step 2 (*cardiology outpatient assessment*) that must precede step 5 (*cardiology assessment*). The sixth step (*physiotherapy assessment*) is optional, and the flow ends with steps 7 (*anesthesia assessment*) and 8 (*assessment by vascular surgeon*) in that order. The ordering of activities in the patient workflow may change because of to resource constraints or interference with other patients. For example, whereas the logical consequence of activities would be A_1,A_2,A_3,A_4,A_5, the order of activities A_2 and A_3 for a particular patient might be altered if there is there is currently no free slot in the radiology department.

16.4 Problem frames analysis

Following the problem frame method [7], we have contained the scenario in an overall context diagram (see Fig. 16.2), showing how the machine to be built fits in the problem world (meaning the hospital, including all technology that is already available as well as the people that work there and the patients).

The solid lines depict interfaces between the domains. Event patterns is a domain that is not given but needs to be designed (hence the single line on the left side of the box) and the coordination support machine is the machine to be developed (hence

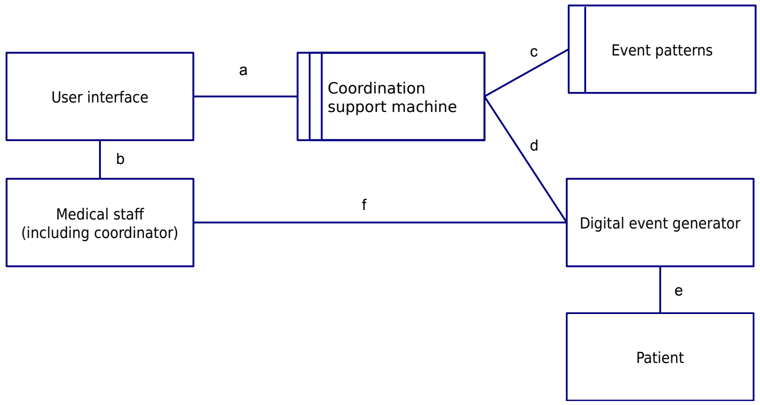

Fig. 16.2 Overall context diagram

the double lines on the left side of the box). The other squares depict other domains that we cannot change.

Interface	Description
a	CSM! [Notification]
b	UI! [View], MS! [Read]
c	EP! [Pattern, Range]
d	DEG! [Generate Event], CSM! [Catch Value]
e	PA! [Factor Evidence]
f	MS! [Factor Evidence]

Table 16.3 Interfaces on the context diagram

In Fig. 16.2 shared events between the domains are an abstraction, the actual elaborate dialogues are not important for this context diagram. The syntax, adopted from [7], denotes that at interface ”a” domain ”CSM” is responsible ”!” for phenomena ”[notification]”.

Catch value is a generic description as we do not know what values we can catch, not what they represent. It can be anything from a stream from an indoor positioning system, to a trigger in an access log or the saving of a dictation. Both the patients and the medical staff create digital traces generated by different digital event generators and these traces are intended to be caught by the coordination support machine.

The relations in Table 16.3 are in general one-way. The reason lies in the nature of the intended system. It is meant to help medical staff to self-coordinate based on situational awareness. This self-coordination is based on getting an overview of the problem world at a glance, the system is not meant to send reminders or use other forms of intrusive communication. At first glance it might seem odd that medical staff has no link to the patients, however, the machine can only capture digital events generated by either the medical staff or the patients and therefore the relation between the two, from a machine point of view, is irrelevant.

Being a type of socio-technical system, the social aspect cannot be neglected. The machine to be built must be able to cope with changes and non-causal and non-deterministic behavior. The main issue is to provide stakeholders with information that has been gathered from multiple systems that each in their way try to represent a piece of the ”real world”. The information to be displayed leads only to biddable interaction, it is always up to a human to decide whether to act upon the displayed information or not.

16.4.1 Problem diagrams

The problem itself is not located in the context diagram and this section will shed some light on the actual problem and the requirements. In this section we loosely follow the approach for mapping role activities to problem frames as described by [5]. By following this approach, we take into consideration the three main factors identified in the case, namely: non- and in-deterministic occurrence of events, context-dependent meaning of events and quality awareness in events. The outcome of the elicitation process is that the coordination support machine is in fact an information display, much like the one described in [8]. In short ”In an Information Display problem the Information Machine is required to monitor the state and behavior of a Real World and to display information about it on a Display”. Fig. 16.3 and Fig. 16.4 are copies of the figures provided in Jackson’s paper and depict a generic decomposed view of the information display.

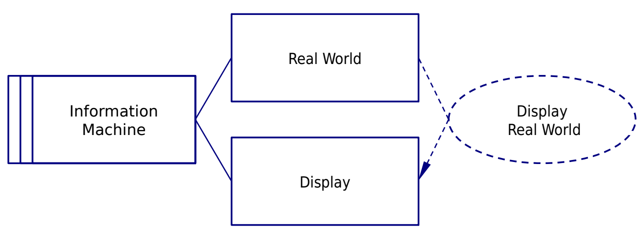

Fig. 16.3 Information Display Problem Diagram (adopted from [8])

16.4.2 Information display

In short, while the patient traverses the activities according to the plan, the information dependencies between the activities are the only hard constraints for the ordering of work. For example, an anesthesiologist cannot conclude his examination without the results of a cardio echo. For some of these activities it is both crucial that the right information be tied to the right patient, but also that the information

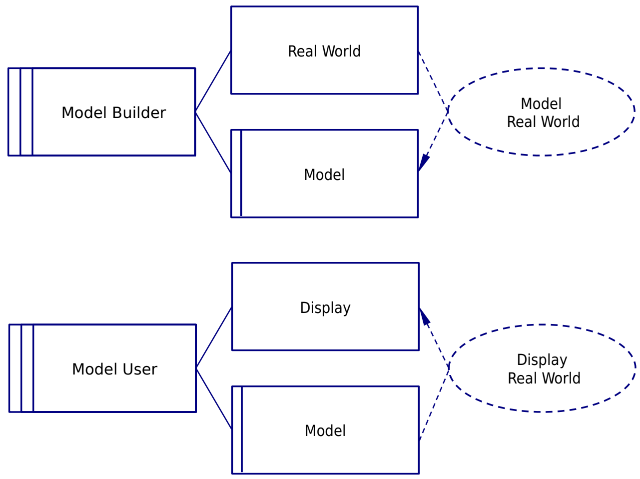

Fig. 16.4 A decomposed view (adopted from [8])

	$\mathbf{A_1}$	$\mathbf{A_2}$	$\mathbf{A_3}$	$\mathbf{A_4}$	$\mathbf{A_5}$	$\mathbf{A_6}$	$\mathbf{A_7}$	$\mathbf{A_8}$
$\mathbf{p_1}$	07:50	08:30	09:15	09:30	10:00	11:45	12:00	13:45
$\mathbf{p_2}$	08:15	09:00	09:45	10:15	11:00	-	13:00	14:15
$\mathbf{p_3}$	08:45	09:30	10:15	10:45	13:00	14:30	14:45	15:00

Table 16.4 Typical schedule for the examination day

from prior steps be available for later activities to proceed. Table 16.4 presents a typical schedule of an examination day of 3 different patients. It represents three patient flows p_i with various activities A_j (i.e. the assessments and examinations) taking place at a pre-defined timeslot. Though each activity can generate events, the clinical systems triggering events are not integrated and are largely unaware of each other. Hence it is not directly possible to automatically gather all this information across multiple sources, let alone display it appropriately.

Displaying a (partial) representation of the real world is a typical information display problem, and fits the Information Display Problem Frame pattern. Wirfs-Brock et al. [17] describe the pattern in slightly different words than Jackson: *"there is some part of the world about whose states and behavior certain information is needed... the problem is to build a machine that will obtain this information and present it at the required place in the required form."* Especially the last words are important for our case, *the required place in the required form*. Ideally we would like to give a 1:1 representation of the real world. However, as we have to rely on incomplete and to a certain degree, unreliable information as a source, this representation is not achievable. We represent the frame concern in Fig. 16.5. Both the figure and the frame concern explanation below are taken from [7, 17] as this explanation fits very well with our case.

The key concern of the Information Display problem frame is that the Information Machine must ensure the Displays output is derived from the values in the

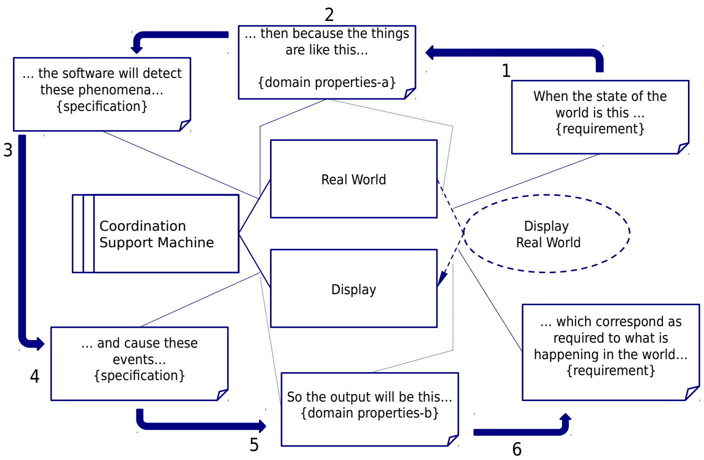

Fig. 16.5 The information display frame concern (adopted from [17])

Real World. Though again, as we at best can give a partial representation of the real world, we need to represent it as well as we can based on the information at hand. We understand that the case caters to at least four flavors of frame variants, as we have description problems, operator problems, connection problems and control problems, each of which each could be represented by its variant. However, as we cannot gain control over many of the factors, as described in earlier sections, we instead propose to accept that we cannot represent the real world in a 1:1 manner and instead we need to represent an x:1 relation where the x needs to be as high as possible (on a 0 to 1 scale). We call this the quality of the representation of the activity. In order to be able to classify the quality of the activity, we need to assign quality attributes to the underlying events as well. The quality of the events is again impacted by the context surrounding the events. The frames concern, illustrated in Fig. 16.5, can be stated as follows:

1. When the Real World is in a particular state
2. THEN because the Real World domain contains particular values
3. AND the Machine will detect those values from the Real World domain
4. AND it causes events to the Display domain
5. AND the Display domain produces some output in response to those events
6. ENSURES the Display can be interpreted as corresponding (as required) to the Real World.

Referring to the case, we can say that the Coordination Support Machine always ensures that the Display responds to the state of the Real World according to the Display Real World requirement:

1. When a digital event generator sends an event
2. THEN the coordination support machine includes this new event

3. AND the events pattern will detect the event and assign it to one or more specific activities
4. AND it adjusts the quality values for all impacted events and activities
5. AND the updated quality is represented on the display per activity
6. ENSURES the most up-to-date representation of the real world Quality of events and activities is an important factor for satisfying the Display Real World requirement. In the next sections we introduce how context impacts the validity of events, and also present a more formal definition of the quality of events.

16.5 Quality awareness for contextualized events

With each situation in the real world, we associate a probability with each of its events to ascertain the possibility that the patient is still in this situation. For example, the *Cardiology outpatient assessment* situation is characterized by the following automatically observable events:

- *ae*: the cardiologist opens the electronic patient record (EPR)
- *dr*: the cardiologist dictates the results of the assessment into the speech recognition software

However, healthcare specialists have different working habits. Some may only open the EPR while the patient is sitting in front of them, or dictate the results while the patient is still present, while other ones open all the patient files in the morning or dictate the results after the patient has left. Hence, the occurrence of a particular event is not a guarantee that the patient is (still) at this location. So, in order to be able to represent the real world for the purpose of serving as a decision support system, we need to introduce a notion of quality to the event. We associate a prior probability of each event in each situation to characterize the possibility that the patient is at this location when this event occurs. These prior probabilities are derived through discussions with the medical stakeholders. For the *Blood sampling* situation this has led to a prior probability of 100% for the *als* and *gbc* events, and a prior probability of 70% for the *dbt* event. This means that the patient is surely at this location when either of the two first events is recognized. However, there is a slight chance that the patient has already left when the last event is triggered.

Ideally, we would use proven probabilistic reasoning techniques like Bayes' probability theory, Zadeh's fuzzy logic or Dempster-Shafer's evidence theory. We investigated each of these techniques but none of them turned out suitable because of pragmatic reasons, such as the maintenance of the knowledge for non-technical experts. With Bayes' theorem, we can compute the probability for a situation S given the events E knowing the probability of the events given the situation.

$$P(S|E) = P(S \cap E)/P(E) = P(E|S) * P(S)/P(E)$$

However, each situation is usually characterized by a set of events:

$$P(S|E_1, E_2, E_3, \ldots) = P(E_1, E_2, E_3, \ldots |S) * P(S)/P(E_1, E_2, E_3, \ldots)$$

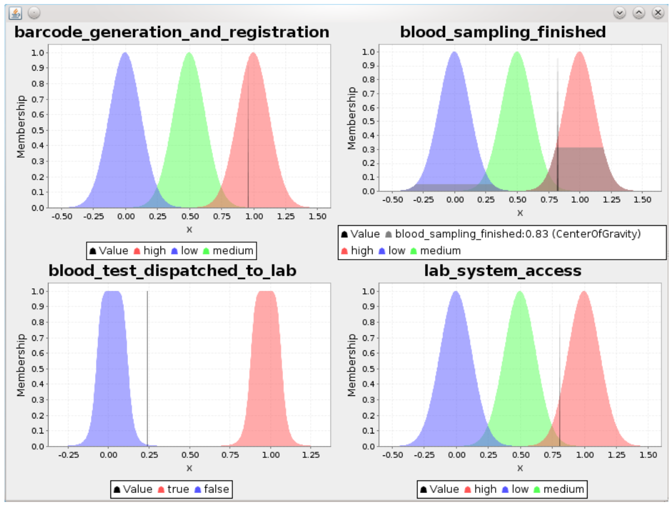

Fig. 16.6 Fuzzy Logic for the Blood Sampling situation

This means that for any set of events we need to know their probability in every situation, and this is guess work without a proper data set from which we can obtain these probabilities.

Zadeh's fuzzy logic has the advantage that it allows you to express domain knowledge with linguistic terms rather than with crisp values. However, various arbitrary choices have to be made, such as the shape of each fuzzy variable (triangle, trapezoid, bell, ...), the modeling of fuzzy sets and rules, as well as the defuzzification into crisp values. Figure 16.6 illustrates this concern for inferring the *blood_sampling_finished* event based on the occurrences of the other observable events (*als, gbc, dbt*) , based on fuzzy rules like the following:

if *(dbt* ***is*** *false)* ***then*** *blood_sampling_finished* ***is*** *low;*

if *(als* ***is*** *medium)* ***and*** *(dbt* ***is not*** *true)* ***then*** *blood˙sampling˙finished* ***IS*** *low;*
...

The evidence theory from Dempster-Share is a generalization of Bayes based on belief and plausibility, but without going into details, experiments with Dempster's combination rule of evidence have shown that it can sometimes lead to counter-intuitive results. Zadeh himself used the following example to illustrate this concern:

```
Doctor A:                      99% brain tumor,    1% meningitis
Doctor B:                      99% concussion,     1% meningitis
Dempster's combination rule:   100% meningitis
```

Obviously, this result is very counter-intuitive. Instead, we pursued a more pragmatic approach. Remember that situation *X* means that the patient is at location *X*. Various events pertain to a particular situation (e.g. *ae*, *cr*, *dr*, ...). Because of the fact that events related to the situation can actually take place before, during or after events, we used prior probabilities to model these uncertainties:

```
P(ar | Radiology examination)      = 1.0
P(ae | Pulmonary examination)      = 0.6
P(dr | Cardiology examination)     = 0.6
```

If predicates of a situation are false, then then particular situation is impossible (likelihood is 0.0). For example, the *Cardiology assessment* cannot take place if the *Cardiology outpatient assessment* has not finished. If all the predicates are true, we compute the probability of the situation based on probability of the last correlated event, and infer the possibility of all the remaining situations. However, this may lead to some mathematical nonsense. Given the likelihoods of the following possible situations:

```
P(Cardiology outpatient assessment) = 0.7    // rr
P(Radiology examination)            = 0.5    // ae
P(Pulmonary assessment)             = 0.5    // ar
```

We see that the sum of the probabilities is not 1. The reason for this behavior is that the related events do not occur all at the same time. If P(X) would be 1.0, we would be absolutely sure that the patient is at that location. However, if it would be 0.95, then there is room for doubt. To solve this problem, we implemented a function $f(x_i)$ (with x_i being the values above) with the following properties:

- Σ f(x_i) = 1.0
- f(1.0) = 1.0 and f(0.0) = 0.0 *(What is absolutely true or false, remains so)*
- Partial ordering of x_i is the same as partial ordering of f(x_i)

The solution is a value z with $f(x_i) = (x_i)^z$ and z such that $\Sigma(x_i)^z = 1.0$. The value z is not easy to compute directly, so we use an iterative method to find the right value.

```
P(A) = 0.99                                 f(P(A)) = 0.948
P(B) = 0.5       with z = 5.265             f(P(B)) = 0.026
P(C) = 0.5                                  f(P(C)) = 0.026
```

The property of the proposed function maintains the weight of the most likely situation while ensuring the transformed values add up to one. We compared our approach with the fuzzy logic method, by capturing the impact for each situation using fuzzy rules like those for the blood sampling event. Our approach classified the location of the patient (by selecting the one with the highest probability) in some cases up to 31% better than with the fuzzy rules. However, we should point out that the outcome of the comparison to some extent depends on set of event traces being used. We also compared the mathematical output and color coding with the experience of medical stakeholders, and while stepping through the trace of events the likelihood of the outcomes were similar to their expectations. Furthermore, the results and methodology were more intuitive and therefore easier to understand by these healthcare professionals. We elaborate more in depth on our approach as well as on the visualization support in our previous works [16, 12].

While testing, we found that cross-cutting work flows greatly impact the handling of events. For the blood sampling activity for example, for coordination purposes one only needs to know if the sample has been taken and if the patient is done with this activity. However, the outcome of the actual lab results is an input for later activities, but it does not impact the flow of the patient though the day.

16.6 Conclusions, lesson learned and further work

Event processing systems are becoming more and more mainstream to continuously monitor behavior and progress in human-in-the-loop systems. For real world decision support in healthcare applications, these systems must account for the inherent uncertain and non-deterministic nature of event occurrences. The major cause of this uncertainty is the gap that exists between the events that happen in real life, and their often incomplete or inaccurate representation with digital event patterns that are being processed by the event based systems.

We found it very useful to apply the problem frame method in order to get a good understanding of the underlying problem of the system. In a typical requirement elicitation we would look into system details and the technical solutions to these problems rather than the actual problem that the *real world* poses. By defining the problem context, we found the need to identify the notion of event quality and an underlying principle for the support system. This clearly sets the boundaries for the technical requirements and our proof-of-concept.

Lessons learned for event quality management and contextualized decision support in the e-health use case are:

- The problem frame methodology is very well suited to identify the gap between the real situation and the digital counterpart.
- We bridged this gap by introducing Quality of Events as a way to measure the trustworthiness of the aggregated information upon which decisions are based.
- The overhead of the probabilistic approach to quality management is negligible with respect to the benefits it brings to ascertain the value of context information.
- In our case study, our approach has shown it can handle different events causing ambiguity because of disagreement about the most likely situation.
- The suggested approach is simple to understand and intuitive so that it can be used by end users without a background in Artificial Intelligence techniques.

Our notion of Quality of Event characterizes how well digital events represent events in the real world. The analysis presented in this chapter provides insight into the diversity of quality requirements that we have to deal with when implementing such a system in medical pre-operative environment. These assessments and requirements are based on real life use cases obtained through various observations and discussions with medical stakeholders in the field.

Additionally, further research should lead to continuous improvements of the quality metrics through feeding the correctness of the inference engine back into the system as input to the original quality metrics. Certain situations can confirm or refute previously recognized situations, thus leading to an improved set of quality metrics based on empirical data, improving upon any statically assigned quality metrics.

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